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USING ARTIFICIAL NEURAL NETWORKS TO STUDY THE DYNAMICS OF POSITIONING SYSTEMS

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ABSTRACT

In this paper the usage of the artificial neural networks instruments for the positioning systems development and for studying its dynamics are described. The described transition from linear differential dynamic equation to architecture of neural network, which reproduces it, ensures the applicability of functional analogy between the structure of linear neuron and the structure of digital filter. These methods are applicable for the many kind of controlled systems, both the homogenous and hybrid type regarding mixing mechanical, electrical, end other types of parts used. In currently researched systems a good reliability of the simulation results are achieved. The described methods are implemented mostly by means of MATLAB environment with the aid of CAD software.

Index Terms - dynamics, artificial, neural, network, positioning, control.

1. INTRODUCTION

Positioning tasks often require taking into account the behavior of moving parts, because of their inertia parameters and the technical solutions used in their design.
In such positioning systems for high efficiency guarantees a variety of methods, including the correcting control signals for actuator movement are used. The very way of correction might be applying common (popular) algorithms, or one that takes into account all or the most of the parameters system design and operation environment can provide. Of course, as takes into account the possibility of implementing such systems on their respective hardware base.
The greatest popularity of certain methods of control algorithms and laws are caused by their multipurpose usedness. They are refined in many applications and implementations of such methods, and they show good results. A detailed study of the whole control system often is considered as inappropriate, especially, given the availability of modern systems with a large number of feedback channels. Through the usage of a large number of sensors, the system is divided into subsystems managed centrally by main control unit with high productivity that is able to perform simultaneous control actions for managing a large number of channels. In addition, usage of standardized components and drives makes possible to design positioning systems and to develop the efficient management procedures for them much easier and simpler.
High popularity of the artificial neural networks apparatus in recent years has added to the existing methods of research facilities another powerful tool. This work focuses on using of artificial neural networks for research and behavior evaluation [4] of positioning systems in time.

2. THE MAIN GOALS

Given the complexities of the full calculation and simulation of systems with many links, the usage of artificial neural networks for modeling of the investigated object to create high-speed model with sufficient compliance with real objects can be considered as more advantageous in some cases. Just making artificial neural network algorithm for a particular management system makes it possible to create complex sophisticated systems that can take into account the particularities of their structure and operation mode. In addition, it is notable that there is the possibility of simple hardware implementation of control systems based on modern components.

3. THE STUDY TASKS

To reach the goal above, it is necessary to follow some important steps:

1. First, we need to have a real control object or create its mathematical model. So, let us assume we have a concrete object or we created its mathematical model. For example, let us use system with DC motor with permanent magnets as control object (Fig. 1).

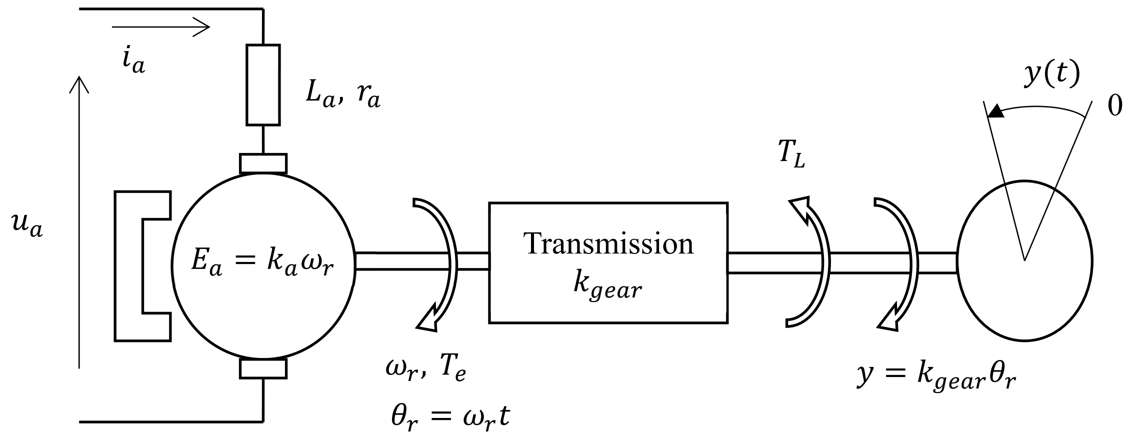


Figure 1. Typical representation of the DC motor with permanent magnets

This kind of motor can be described by following equations:

$$\begin{cases} \frac{di_a}{dt} = \frac{1}{L_a}(-r_a i_a - k_a\omega_r + u_a), \\ \frac{d\omega_r}{dt} = \frac{1}{J}(T_e - T_v - T_L) = \frac{1}{J}(k_a i_a - B_m\omega_r - T_L), \\ \frac{d\theta_r}{dt} = \omega_r, \\ y(t) = k_{gear}\theta_r(t). \end{cases} \quad (1)$$

here i_a is armature current, u_a is applied voltage, r_a is armature resistance, L_a is armature inductance, k_a is torque constant, ω_r is rotor angular velocity, T_e is electromagnetic torque, T_L is load torque, B_m is damping coefficient, J is rotor inertia and T_v is motor torque.

In this case the motor mathematical model as controlled object ii used for neural controller artificial network architecture formation. Therefore, the real quantities parameters did not influence at the artificial neural network structure.

With some assumptions and optimizations, system (1) can be transformed into Laplace operator form (operator $s = \frac{d}{dt}$):

$$\begin{cases} \left(s+\frac{r_a}{L_a}\right)I_a(s) = -\frac{k_a}{L_a}\Omega_r(s)+\frac{1}{L_a}U_a(s), \\ \left(s+\frac{B_m}{J}\right)\Omega_r(s) = \frac{1}{J}k_aI_a(s)-\frac{1}{J}T_L(s), \\ s\Theta_r(s) = \Omega_r(s), \\ Y(s) = k_{gear}\Theta_r(s). \end{cases} \tag{2}$$

And, finally, transfer function of the control object can be obtained from (2):

$$G_{servo}(s) = \frac{Y(s)}{U_a(s)} = \frac{k_{gear}k_a}{s\left(L_aJs^2+(r_aJ+L_aB_m)s+r_aB_m+k_a^2\right)} \tag{3}$$

2. In accordance with the selected law of the control, we form the controller structure, which is defined by delay lines.

In many cases, positioning system can be described as the conversion unit that convert reference signal to output parameter value (Fig. 2).

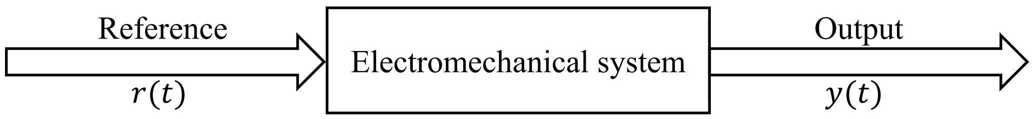


Figure 2. Simple representation of typical control system

According to the general control theory many processes can be represented as the simple control loop (Fig. 3)

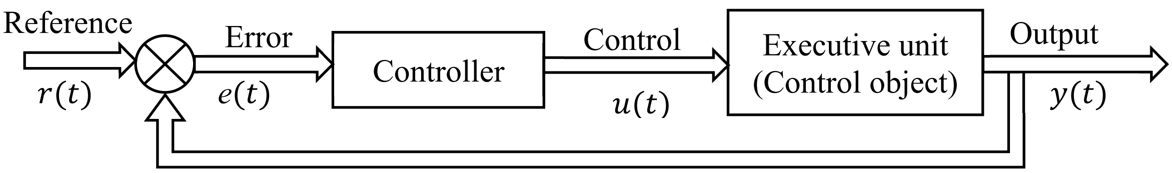


Figure 3. Simple control system

For the linear transfer function of the positioning system that developers often choose:

$$G_{sys}(s) = G_{control}(s)G_{servo}(s) = \frac{Y(s)}{R(s)} = 1, \text{(or any constant coefficient)} \tag{4}$$

In accordance to (4), ideal controller for this example should have transfer function is as follow:

$$G_{control}(s) = \frac{1}{G_{servo}(s)} = \frac{s\left(L_aJs^2+(r_aJ+L_aB_m)s+r_aB_m+k_a^2\right)}{k_{gear}k_a} =$$
$$= \frac{L_aJ}{k_{gear}k_a}s^3+\frac{r_aJ+L_aB_m}{k_{gear}k_a}s^2+\frac{r_aB_m+k_a^2}{k_{gear}k_a}s \tag{5}$$

After Z-transformation (operator $s = \frac{T_s}{1-z^{-1}}$) of (5) one have:

$$G_{control}(z) = \frac{U(z)}{E(z)} = \frac{k_{12}z^{-2}+k_{11}z^{-1}+k_{10}}{k_{23}z^{-3}+k_{22}z^{-2}+k_{21}z^{-1}+k_{20}}, \tag{6}$$

here $U(z)$ is a discrete output signal from controller to object, $E(z)$ is a discrete error signal for controller, T_s is a discretization time step,

$$k_{12} = -T_sk_a^2-B_mT_sr_a\,,$$
$$k_{11} = 2T_sk_a^2+2B_mT_sr_a+B_mL_aT_s^2+JT_s^2r_a,$$
$$k_{10} = -T_sk_a^2-B_mT_sr_a-B_mL_aT_s^2-JL_aT_s^3-JT_s^2r_a,$$
$$k_{23} = k_ak_{gear},$$

$$k_{23}u_{k-3} + k_{22}u_{k-2} + k_{21}u_{k-1} + k_{20}u_k = k_{12}e_{k-2} + k_{11}e_{k-1} + k_{10}e_k \quad (8)$$

$$k_{20}u_k = k_{12}e_{k-2} + k_{11}e_{k-1} + k_{10}e_k - k_{23}u_{k-3} - k_{22}u_{k-2} - k_{21}u_{k-1} \quad (9)$$

$$u_k = w_{13}e_{k-2} + w_{12}e_{k-1} + w_{11}e_k + w_{16}u_{k-3} + w_{15}u_{k-2} + w_{14}u_{k-1} \quad (10)$$

here, $u_k, u_{k-1}, u_{k-2}, u_{k-3}, e_k, e_{k-1}, e_{k-2}$ are discrete values of the output signal and error by time steps, $w_{11} = \frac{k_{10}}{k_{20}}$, $w_{12} = \frac{k_{11}}{k_{20}}$, $w_{13} = \frac{k_{12}}{k_{20}}$, $w_{14} = -\frac{k_{21}}{k_{20}}$, $w_{15} = -\frac{k_{22}}{k_{20}}$, $w_{16} = -\frac{k_{23}}{k_{20}}$. Therefore, there was obtained information about the artificial neural network structure of designed controller (Fig. 4). For the current example we trained this controller for using with DC motor which has parameters as follows: r_a=200 Ohm, L_a=0.002 H, k_a=0.2 V*s/rad (N*m/A), J=0.00000002 kg*m^2 , B_m=0.00000005 N*m*s/rad, k_{gear}=0.01.

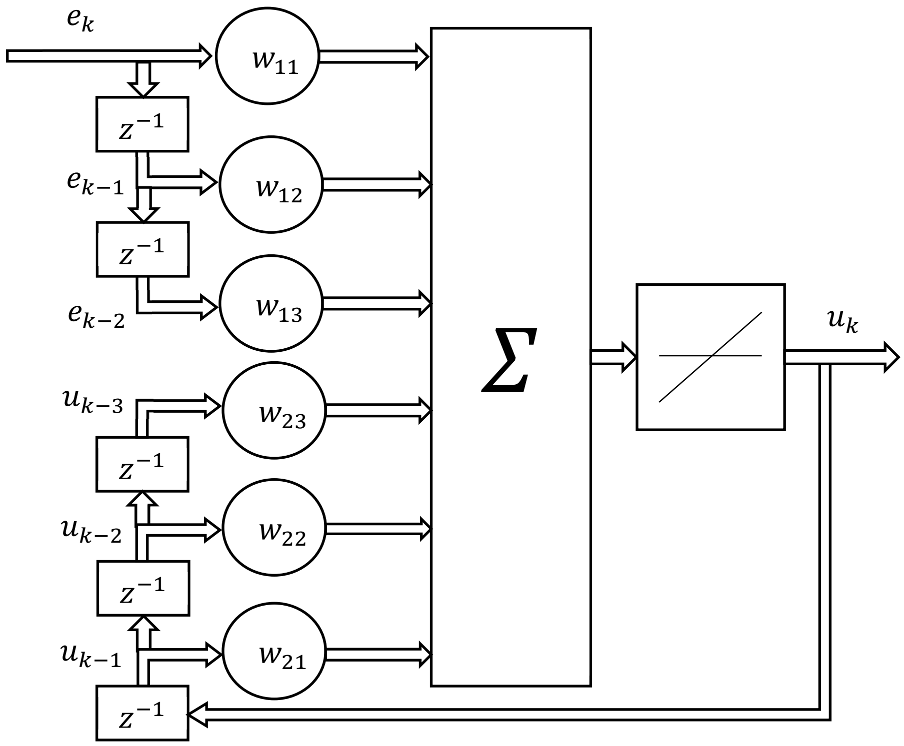


Figure 4. Basic architecture of the artificial neural network for controller

3. We select the mathematical model of the reference based on the desirable dynamics of the controlled object that sets a duration of the transient process. There is possible over control to reach necessary parameters of the control law.
4. A reference provides a creation of the proper sequence that is used for the controller training. It is necessary to have numerical sequences on both an input and output of the object. All numerical sequences are stored in the computer memory.
5. A goal of the training is to select such weighing coefficients for all neurons of the controller that provide a minimum of the possible divergence between the output signals of the object and the reference.
6. A desired structure is prepared after the training procedure completion, and values of weighing coefficients and the duration of delays are carried in the Simulink environment.
7. The convergence of signals from the reference outputs and the object, managed by synthesized controller, is compared.
8. Finally, the controller is joined with the object, and the duration of both the transient process and delays, and a quality of reacting on the indignation (working off) are observed as well.

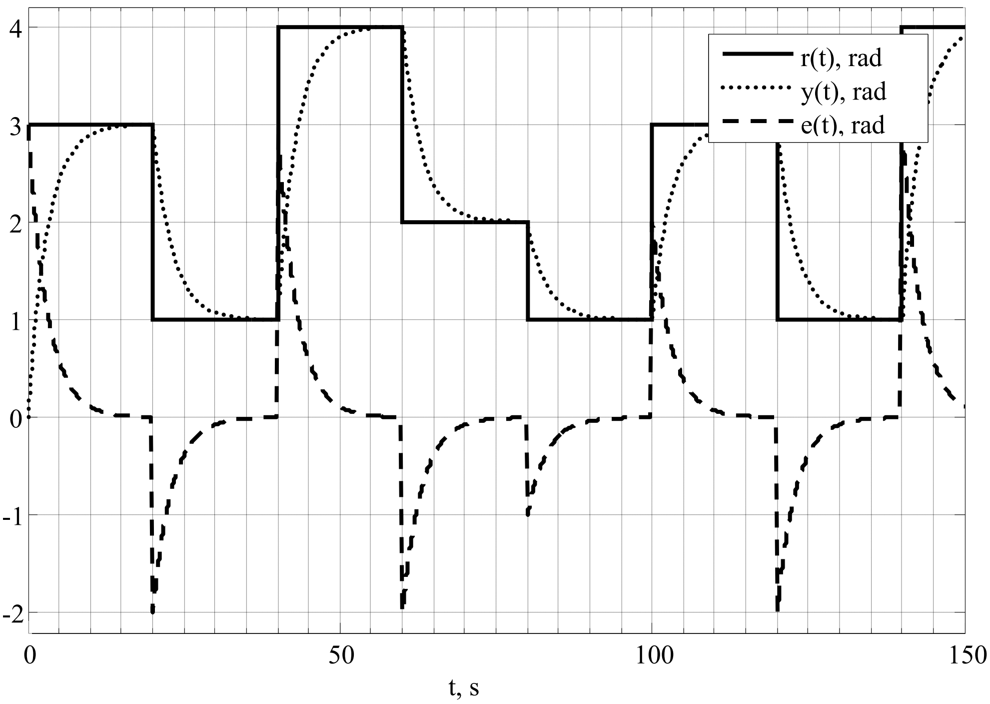


Figure 5. Closed control loop simulation of the positioning system.

Obviously [1, 2], the difference signal created by the output signal of a system and the reference signal is applied to the input of a neural controller. In order to improve the dynamic characteristics, we use two separated inputs (ports), i.e., an output signal of a system is applied to one input (port), while the input signal of the reference is applied to other input (port). Simulation research has shown that in this case the discrepancy between the output signals of the reference and the system as well is smaller than in case of using a traditional architecture of input circuit of a neural controller. So, it was proposed [3] to feed in the controller adder separately the reference signal r_k and its corresponding delays r_{k-1}, r_{k-2} , as well as the output signal y_k and its corresponding delays y_{k-1}, y_{k-2} instead the error $\Delta y_k = (r_k - y_k)$ on k-th step of the controlling process and its previous (delayed) values Δy_{k-1}, Δy_{k-2} in *(k-1)* and *(k-2)* steps.

The equation that describes the operation of the neural controller with two-port separated inputs (Fig. 6) looks as follows:

$$\begin{aligned} u_k &= w_{11} r_k + w_{12} r_{k-1} + w_{13} r_{k-2} + \\ &+ w_{14} y_k + w_{15} y_{k-1} + w_{16} y_{k-2} + w_{17} u_{k-1} \end{aligned} \tag{11}$$

Obviously, at $w_{14} = -w_{11}$, $w_{15} = -w_{12}$, $w_{16} = -w_{13}$ this scheme(see Fig. 6) is equivalent to the scheme with single input for positioning. However during the training, the coefficients for individual inputs are set independently of each other, so it is possible to supply the control action to the object outside the circle of feedback. The value of the weight coefficient w_{17} is assumed to be always fixed and equal to 1.

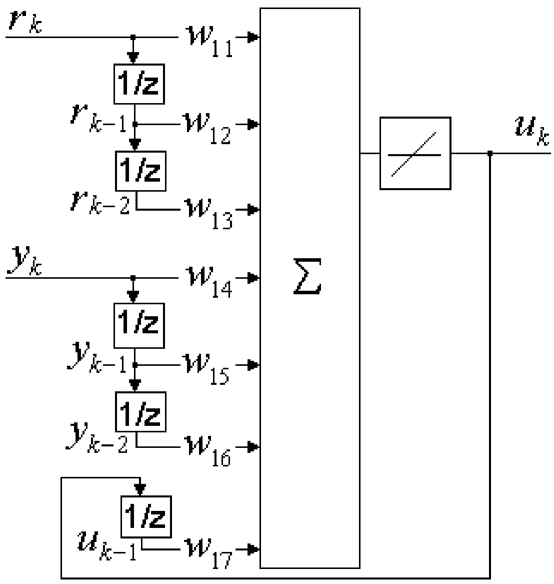
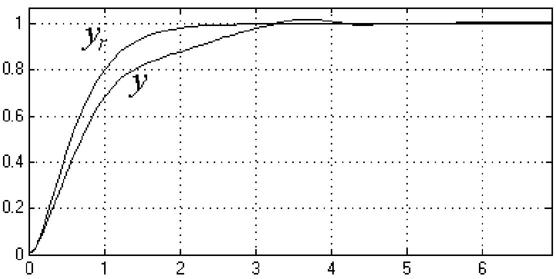
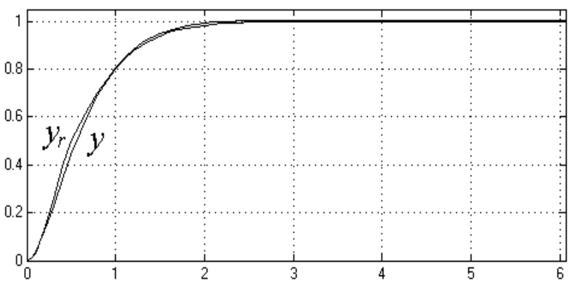


Figure 6. Structure of a neural controller with separated inputs

Comparison of the output signals of the reference and the object controlled by such a controller (Fig. 7, b) shows that the system possesses better dynamic characteristics, so it confirms the feasibility of using the controller with separated inputs.



a)



b)

Figure 7. Comparing the output signals of the reference y_r and the system with the neural controller y (a – the one-port input and b – the two-port input, respectively)

In the worst case, the difference between output signals mentioned above, was equal 14.3% for the common structure of controller, and it was equal 7.1% for a controller with separate inputs. The training duration was the same for both structures and it did not exceed 1 minute.

One of the perspective applications for a developed automatic control system based on the neural controller is the acquisition of multimedia data in wireless sensor networks as n important segment of that system.

4. CONCLUSIONS

The methods of analysis of the dynamics of positioning using single and multi-layered artificial neural network models to create models of the study objects of positioning in complex systems modeling with the aid of the finite element method as a base, as one of the most reliable and adequate modeling tools is used for the sophisticated systems. The data source for relevant training artificial neural networks can also be the data, obtained during the experiments with real systems.

This workaround may be useful for creating and analyzing virtual and real models for positioning systems with sufficient speed and real good compliance. In addition, it saves time and resources to conduct such studies with real systems. As well as, using artificial neural networks gives a number of advantages compared to traditional analysis. Such as the ability of the existing model training to obtain one a similar to the object or modify basic artificial neural network for additional capacity or correction of system behavior in the event of a significant divergence from the real object due to changes in operating conditions, wear elements, and so on.

Currently, the range of supported devices designs and technologies our methods work with are the micro positioning systems and with limited number of parts and some types of microsystem devices. It is mainly because there are currently extremely large numbers of designs and technologies that all have different approaches to study and to model them. To describe every last of them requires considerable amount of research work and experimental study of its functional principles.

The described methods are implemented mostly by means of MATLAB environment, making them available for evaluation and implementing by wide range of users.

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